Polish Companies Bankruptcy

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In [117]:

```
from IPython.display import Image
from IPython.core.display import HTML
Image(url= "https://s.yimg.com/ny/api/res/1.2/vQGqpL_guzGrlKkOeXz8Qg--
~A/YXBwaWQ9aGlnaGxhbmRlcjtzbT0xO3c9ODAw/https://media.zenfs.com/en-
US/homerun/motleyfool.com/8c3d0a8777ac8a399c78bad86ee74b39", width=600, height=200)
```

Out[117]:

Introduction:

The Polish Companies Bankruptcy Data Set (http://archive.ics.uci.edu/ml/datasets/Polish+companies+bankruptcy+data) will be used for building a classification model to predict companies that will bankrupt. Visit the link for the details of this dataset.

Algorithms:

- Logistic Regression
- Linear SVM
- Decision Tree
- Random Forest

In [1]:

```
# to read the zip file
from zipfile import ZipFile

# specifying the zip file name
data = "data.zip"

# opening the zip file in READ mode
with ZipFile(data, 'r') as zip:
    # printing all the contents of the zip file
    zip.printdir()
    zip.extractall()
    zips = zip.namelist()
```

```
File Name                                             Modified             Size
1year.arff                                     2016-04-11 08:38:14      3432892
2year.arff                                     2016-04-11 08:38:14      4987459
3year.arff                                     2016-04-11 08:38:16      5169674
4year.arff                                     2016-04-11 08:38:16      4829865
5year.arff                                     2016-04-11 08:38:16      2899490
```

In [2]:

```
# importing libraries
from scipy.io import arff
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from termcolor import colored
from sklearn import model_selection
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import Imputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn import model_selection
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
import warnings
warnings.filterwarnings("ignore")
```

In [3]:

```
# extract from each arff file
data1= []
for i,j in enumerate(zips):
    data = arff.loadarff(zips[i])
    data1.append(pd.DataFrame(data[0]))
```

In [74]:

```
# brief view of the year 1, 2, and 3
print(colored("Year 1:\n", "red"), data1[0].head(), colored("\nlength:", "blue"), len(data1[0]),
      colored("\n\nYear 2:\n", "red"), data1[1].head(), colored("\nlength:", "blue"), len(data1[1])
,
      colored("\n\nYear 3:\n", "red"), data1[2].head(), colored("\nlength:", "blue"), len(data1[2])
)
```

```
Year 1:
      Attr1    Attr2    Attr3   Attr4    Attr5    Attr6     Attr7    Attr8  \
0  0.200550  0.37951  0.39641  2.0472  32.3510  0.38825  0.249760  1.33050
1  0.209120  0.49988  0.47225  1.9447  14.7860  0.00000  0.258340  0.99601
2  0.248660  0.69592  0.26713  1.5548  -1.1523  0.00000  0.309060  0.43695
3  0.081483  0.30734  0.45879  2.4928  51.9520  0.14988  0.092704  1.86610
4  0.187320  0.61323  0.22960  1.4063  -7.3128  0.18732  0.187320  0.63070

    Attr9   Attr10  ...     Attr56   Attr57   Attr58    Attr59  Attr60  Attr61  \
0  1.1389  0.50494  ...   0.121960  0.39718  0.87804  0.001924  8.4160  5.1372
1  1.6996  0.49788  ...   0.121300  0.42002  0.85300  0.000000  4.1486  3.2732
2  1.3090  0.30408  ...   0.241140  0.81774  0.76599  0.694840  4.9909  3.9510
3  1.0571  0.57353  ...   0.054015  0.14207  0.94598  0.000000  4.5746  3.6147
4  1.1559  0.38677  ...   0.134850  0.48431  0.86515  0.124440  6.3985  4.3158

    Attr62  Attr63   Attr64  class
0   82.658  4.4158   7.4277   b'0'
1  107.350  3.4000  60.9870   b'0'
2  134.270  2.7185   5.2078   b'0'
3   86.435  4.2228   5.5497   b'0'
4  127.210  2.8692   7.8980   b'0'

[5 rows x 65 columns]
length: 7027

Year 2:
      Attr1    Attr2     Attr3   Attr4    Attr5     Attr6    Attr7    Attr8  \
0  0.202350  0.46500  0.240380  1.5171  -14.547  0.510690  0.25366  0.91816
1  0.030073  0.59563  0.186680  1.3382  -37.859 -0.000319  0.04167  0.67890
2  0.257860  0.29949  0.665190  3.2211   71.799  0.000000  0.31877  2.33200
3  0.227160  0.67850  0.042784  1.0828  -88.212  0.000000  0.28505  0.47384
4  0.085443  0.38039  0.359230  1.9444   21.731  0.187900  0.10823  1.37140
```

```
     Attr9   Attr10  ...   Attr56    Attr57   Attr58   Attr59  Attr60  \
0  1.15190  0.42695  ...  0.13184  0.473950  0.86816  0.00024  8.5487
1  0.32356  0.40437  ...  0.12146  0.074369  0.87235  0.00000  1.5264
2  1.67620  0.69841  ...  0.16499  0.369210  0.81614  0.00000  4.3325
3  1.32410  0.32150  ...  0.29358  0.706570  0.78617  0.48456  5.2309
4  1.11260  0.52167  ...  0.10124  0.163790  0.89876  0.00000  5.7035

    Attr61   Attr62   Attr63   Attr64  class
0  5.16550  107.740  3.38790   5.3440   b'0'
1  0.63305  622.660  0.58619   1.2381   b'0'
2  3.19850   65.215  5.59690  47.4660   b'0'
3  5.06750  142.460  2.56210   3.0066   b'0'
4  4.00200   89.058  4.09840   5.9874   b'0'

[5 rows x 65 columns]
length: 10173

Year 3:
      Attr1    Attr2    Attr3   Attr4    Attr5    Attr6     Attr7   Attr8  \
0  0.174190  0.41299  0.14371  1.3480 -28.9820  0.60383  0.219460  1.1225
1  0.146240  0.46038  0.28230  1.6294   2.5952  0.00000  0.171850  1.1721
2  0.000595  0.22612  0.48839  3.1599  84.8740  0.19114  0.004572  2.9881
3  0.024526  0.43236  0.27546  1.7833 -10.1050  0.56944  0.024526  1.3057
4  0.188290  0.41504  0.34231  1.9279 -58.2740  0.00000  0.233580  1.4094

    Attr9   Attr10  ...    Attr56    Attr57   Attr58    Attr59  Attr60  \
0  1.1961  0.46359  ...  0.163960  0.375740  0.83604  0.000007  9.7145
1  1.6018  0.53962  ...  0.027516  0.271000  0.90108  0.000000  5.9882
2  1.0077  0.67566  ...  0.007639  0.000881  0.99236  0.000000  6.7742
3  1.0509  0.56453  ...  0.048398  0.043445  0.95160  0.142980  4.2286
4  1.3393  0.58496  ...  0.176480  0.321880  0.82635  0.073039  2.5912

   Attr61   Attr62  Attr63  Attr64  class
0  6.2813   84.291  4.3303  4.0341   b'0'
1  4.1103  102.190  3.5716  5.9500   b'0'
2  3.7922   64.846  5.6287  4.4581   b'0'
3  5.0528   98.783  3.6950  3.4844   b'0'
4  7.0756  100.540  3.6303  4.6375   b'0'

[5 rows x 65 columns]
length: 10503
```

In [35]:

```python
# concatenate years 1,2,3
df = pd.concat([data1[0], data1[1], data1[2]])
print("Data size:", df.shape)
```

```
Data size: (27703, 65)
```

In [36]:

```python
# the only column whose values are extremely high, so better to drop it
print(df["Attr55"].head())
df["Attr55"] = None
```

```
0    348690.0
1      2304.6
2      6332.7
3     20545.0
4      3186.6
Name: Attr55, dtype: float64
```

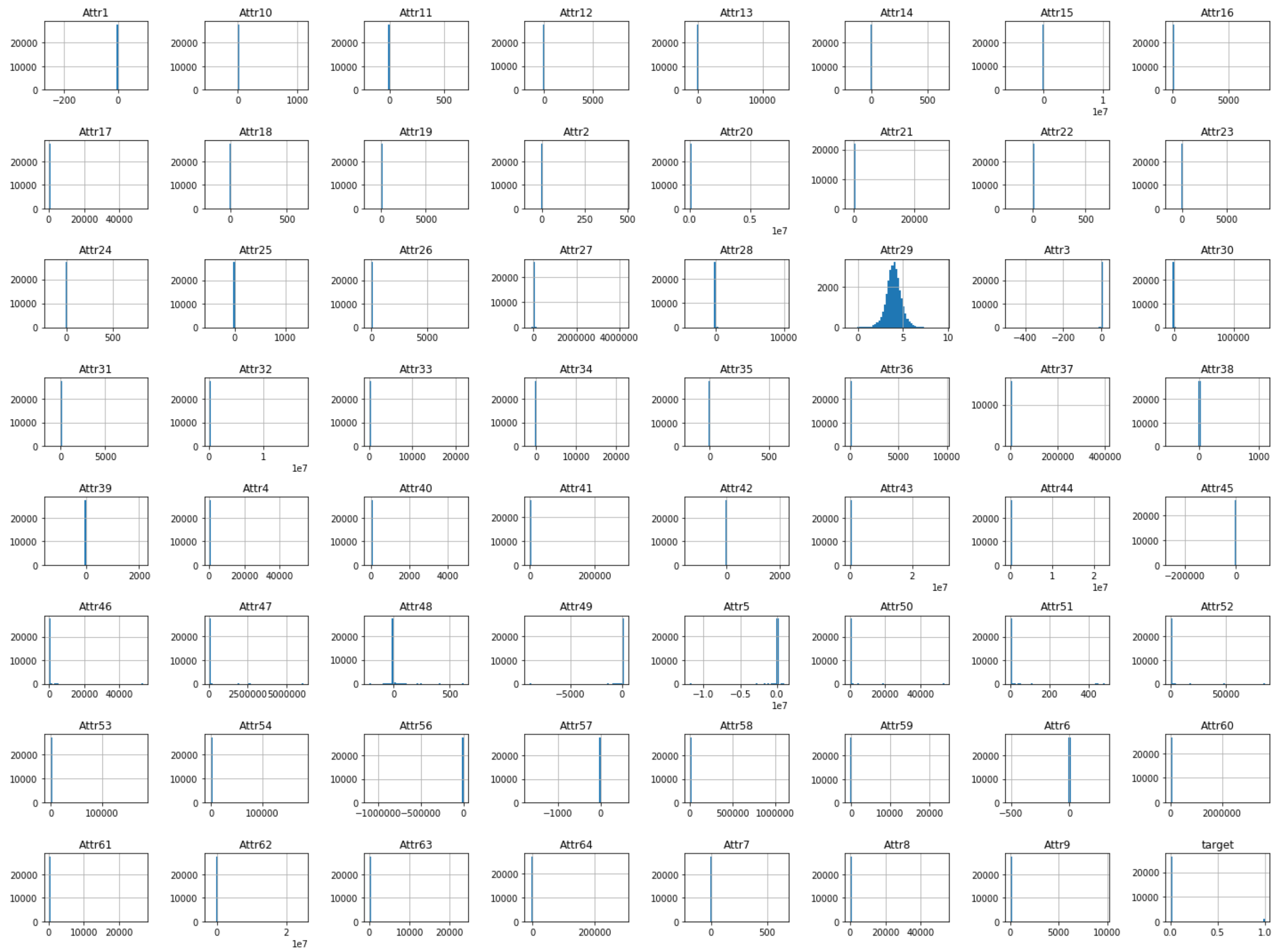
In [32]:

```python
# rearrange target column
print("Null values in class:", df['class'].isnull().sum())
df.rename(columns={'class':'target'}, inplace=True)
df.replace({'target': b'1'}, int(1), inplace=True)
df.replace({'target': b'0'}, int(0), inplace=True)
print(df['target'].value_counts())
```

```
Null values in class: 0
0    26537
1     1166
Name: target, dtype: int64
```

In [33]:

```
# to view distribution
df.hist(bins=50, figsize=(20,15))
plt.tight_layout()
plt.show()
```



In [19]:

```
# splitting into df and target
target = df.iloc[:, -1]
df = df.drop(df.columns[-1], axis=1)
```

In [20]:

```
# the data must be preprocessed (remove duplicates and null values with 50 null required,
# and then to use Imputation transformer for completing missing values)
imr=Imputer(missing_values='NaN', strategy='median', axis=0)
imr=imr.fit(df)
imputed=imr.transform(df.values)
df=pd.DataFrame(pd.DataFrame(imputed).values,columns=["Attr1","Attr2","Attr3","Attr4","Attr5","Attr
6","Attr7","Attr8",
                                                   "Attr9","Attr10","Attr11","Attr12","Attr13","Attr14
"Attr15","Attr16",
                                                   "Attr17","Attr18","Attr19","Attr20","Attr21","Attr2
,"Attr23","Attr24",
                                                   "Attr25","Attr26","Attr27","Attr28","Attr29","Attr3
,"Attr31","Attr32",
                                                   "Attr33","Attr34","Attr35","Attr36","Attr37","Attr3
,"Attr39","Attr40",
```

```
                                                  "Attr41","Attr42","Attr43","Attr44","Attr45","Attr4
,"Attr47","Attr48",
                                                  "Attr49","Attr50","Attr51","Attr52","Attr53","Attr5
,"Attr55","Attr56",
                                                  "Attr57","Attr58","Attr59","Attr60","Attr61","Attr6
,"Attr63","Attr64"])
```

In [21]:

```
# splitting into train-test
seed = 42 #memory location for all methods
X, y = df, target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=seed)
print("Original dataset:", len(X_train), "train +", len(X_test), "test")
```

```
Original dataset: 22162 train + 5541 test
```

In [77]:

```
# other option to decorate the text
class color:
   PURPLE = '\033[95m'
   CYAN = '\033[96m'
   DARKCYAN = '\033[36m'
   BLUE = '\033[94m'
   GREEN = '\033[92m'
   YELLOW = '\033[93m'
   RED = '\033[91m'
   BOLD = '\033[1m'
   UNDERLINE = '\033[4m'
   END = '\033[0m'
```

In [79]:

```
# StandardScaler
X_sc = pd.DataFrame(StandardScaler().fit_transform(X_train))
print(color.BOLD+"After scaling: \n"+color.END, X_sc.head())
```

After scaling:

```
          0         1         2         3         4         5         6  \
0 -0.009919 -0.040815  0.015552 -0.049748  0.008922  0.010280 -0.019611
1  0.083552 -0.099216  0.103489  0.303825  0.012503  0.107126  0.008571
2 -0.004570  0.047077 -0.056525 -0.075919  0.007928  0.010280 -0.016897
3 -0.123384  0.063264 -0.043736 -0.073388  0.009365  0.008845 -0.055874
4  0.020391  0.000477  0.009987 -0.062376  0.009115  0.062168 -0.005647

         7         8         9   ...        54        55        56        57  \
0 -0.022954 -0.025938 -0.003328  ... -0.107389  0.006853  0.000923 -0.007612
1  0.024262 -0.026393  0.016307  ... -0.033344  0.006850  0.015226 -0.007608
2 -0.027522 -0.014807 -0.032890  ... -0.120082  0.006831  0.018272 -0.007583
3 -0.027856  0.002672 -0.038334  ... -0.108266  0.006956 -0.184418 -0.007713
4 -0.026012  0.005283 -0.017216  ... -0.095513  0.006827  0.015059 -0.007584

          58        59        60        61        62        63
0 -0.010275 -0.015382 -0.044478 -0.010109 -0.034787 -0.034097
1 -0.011629 -0.015219 -0.046220 -0.010507  0.087117 -0.033427
2 -0.000777 -0.015277  0.048645 -0.009972 -0.040646 -0.033517
3  0.022886 -0.014758  0.030610 -0.010248 -0.024130 -0.032281
4 -0.011324 -0.014419 -0.025652 -0.010259 -0.022904 -0.028869

[5 rows x 64 columns]
```

In [13]:

```
# MinMaxScaler
X_scaled =  pd.DataFrame(MinMaxScaler().fit_transform(X))
print(color.BOLD+"After scaling: \n"+color.END, X_scaled.head())
```

After scaling:

```
          0         1         2         3         4         5         6  \
0  0.732097  0.131149  0.965215  0.000038  0.923152  0.626537  0.226290
```

```
1  0.732122  0.131367  0.965367  0.000036  0.923151  0.626059  0.226300
2  0.732234  0.131721  0.964955  0.000029  0.923150  0.626059  0.226361
3  0.731758  0.131019  0.965340  0.000047  0.923154  0.626244  0.226103
4  0.732059  0.131572  0.964879  0.000026  0.923149  0.626290  0.226216

          7         8         9  ...        54        55        56       57  \
0  0.002664  0.000242  0.304174  ...  0.347200  0.999736  0.751235  0.00018
1  0.002658  0.000299  0.304169  ...  0.291364  0.999736  0.751246  0.00018
2  0.002648  0.000259  0.304046  ...  0.292013  0.999736  0.751425  0.00018
3  0.002674  0.000233  0.304217  ...  0.294304  0.999736  0.751120  0.00018
4  0.002651  0.000243  0.304099  ...  0.291506  0.999736  0.751274  0.00018

         58        59        60        61        62        63
0  0.013563  0.000002  0.000436  0.085425  0.000204  0.034980
1  0.013563  0.000001  0.000367  0.085426  0.000161  0.035155
2  0.013592  0.000001  0.000392  0.085427  0.000132  0.034972
3  0.013563  0.000001  0.000380  0.085425  0.000196  0.034973
4  0.013568  0.000002  0.000406  0.085426  0.000138  0.034981

[5 rows x 64 columns]
```

In [48]:

```python
# scaled train-test split
X_train_sc, X_test_sc, y_train, y_test = train_test_split(X_sc, y, test_size=0.2, random_state=seed
)
X_train_scaled, X_test_scaled, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, rando
m_state=seed)
print(len(X_train_sc), "train +", len(X_test_sc))
```

```
22162 train + 5541
```

Review (1)

The data of year 1, 2, 3 have been concatenated and then scaled using Standard and MinMax. The dataset was split into train and test for each conditions and they will be compared after.

- unscaled
- StandardScaler
- MinMaxScaler

The target column is very unproportional since there are about 26000 0's while only about 1100 1's. Although, it makes sense with this data since it's of bankruptcy.

In [68]:

```python
# classifiers for predicting model
classifier_namess = ["Logistic Regression", "Linear SVM", "Decision Tree", "Random Forest"]
classifiers = [LogisticRegression(), LinearSVC(), DecisionTreeClassifier(), RandomForestClassifier
()]
```

In [53]:

```python
# unscaled scores
cross_val_scores = []
for classifier in classifiers:
    classifier_names = classifier.fit(X_train, y_train) #fit trains the model
    scores = cross_val_score(classifier, X_train, y_train, cv=10) #10-fold cv
    cross_val_scores.append(np.mean(scores))
print("Classifiers:", classifier_namess)
print("Cross-Validation:", cross_val_scores)
```

```
Classifiers: ['Logistic Regression', 'Linear SVM', 'Decision Tree', 'Random Forest']
Cross-Validation: [0.945357615226482, 0.8970821407734814, 0.9525309760103285, 0.9629999663995943]
```

In [56]:

```python
# Bagging of the classifiers (unscaled)
for i, classifier in enumerate(classifiers):
```

```
    bg = BaggingClassifier(classifier, max_samples=0.5, max_features=1.0, n_estimators=20, random_s
tate=seed)
    bg.fit(X_train, y_train)
    print("Bagging of {}".format(classifier_namess[i]), bg.score(X_test, y_test))
```

```
Bagging of Logistic Regression 0.9518137520303195
Bagging of Linear SVM 0.9474824038982134
Bagging of Decision Tree 0.971304818624797
Bagging of Random Forest 0.9626421223605848
```

In [66]:

```
# StandardScaler scores
cross_val_scoress = []
for classifier in classifiers:
    classifier_names = classifier.fit(X_train_sc, y_train) #fit trains the model
    scores = cross_val_score(classifier, X_train_sc, y_train, cv=10) #10-fold cv
    cross_val_scoress.append(np.mean(scores))
print("Classifiers:", classifier_namess)
print("Cross-Validation:", cross_val_scoress)
```

```
Classifiers: ['Logistic Regression', 'Linear SVM', 'Decision Tree', 'Random Forest']
Cross-Validation: [0.9570887997629646, 0.9569986284925329, 0.9503640553042313, 0.9627288823995986]
```

In [58]:

```
# Bagging of the classifiers (StandardScaler)
for i, classifier in enumerate(classifiers):
    bg = BaggingClassifier(classifier, max_samples=0.5, max_features=1.0, n_estimators=20, random_s
tate=seed)
    bg.fit(X_train_sc, y_train)
    print("Bagging of {}".format(classifier_namess[i]), bg.score(X_test_sc, y_test))
```

```
Bagging of Logistic Regression 0.9581303013896408
Bagging of Linear SVM 0.9577693557119653
Bagging of Decision Tree 0.9698610359140949
Bagging of Random Forest 0.962461649521747
```

In [67]:

```
# MinMaxScaler scores
cross_val_scoresss = []
for classifier in classifiers:
    classifier_names = classifier.fit(X_train_scaled, y_train) #fit trains the model
    scores = cross_val_score(classifier, X_train_scaled, y_train, cv=10) #10-fold cv
    cross_val_scoresss.append(np.mean(scores))
print("Classifiers:", classifier_namess)
print("Cross-Validation:", cross_val_scoresss)
```

```
Classifiers: ['Logistic Regression', 'Linear SVM', 'Decision Tree', 'Random Forest']
Cross-Validation: [0.9577205281169212, 0.9577656341160191, 0.930375988539207, 0.9557798297783086]
```

In [96]:

```
# Bagging of the classifiers (MinMaxScaler)
for i, classifier in enumerate(classifiers):
    bg = BaggingClassifier(classifier, max_samples=0.5, max_features=1.0, n_estimators=10, random_s
tate=seed)
    bg.fit(X_train_scaled, y_train)
    print("Bagging of {}".format(classifier_namess[i]), bg.score(X_test_scaled, y_test))
```

```
Bagging of Logistic Regression 0.9584912470673164
Bagging of Linear SVM 0.9584912470673164
Bagging of Decision Tree 0.9574084100342899
Bagging of Random Forest 0.9579498285508031
```

Review (2)

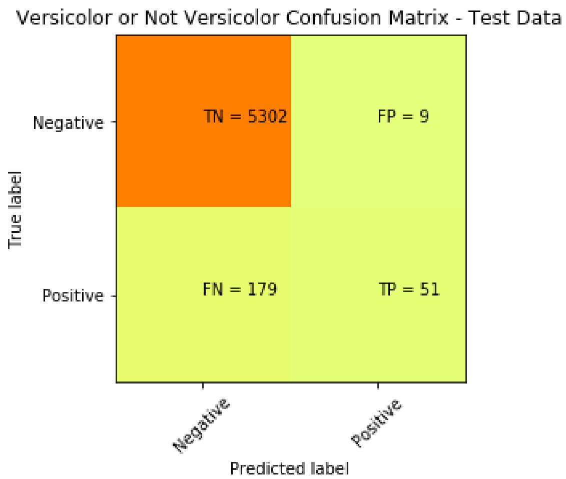
The scores of each classifier can be seen above. Highest scores:

- Unscaled: Random Forest 96.3%
  - **Bagging of Decision Tree 97.13%**
- StandardScaler: Random Rorest 96.24%
  - **Bagging of Decision Tree 96.99%**
- MinMaxScaler: Linear SVM 96.24%
  - Bagging of Random Forest 95.92% (they were all around 95.8%)

Bagging ensemble increased the scores for most. The best method tested for this dataset is Bagging of DecisionTree unscaled with cv of 10-fold with an accuracy of 97.13%, and the next best was Bagging of DecisionTree StandardScaler with an accuracy of 96.99%. Most of the scores were were above 95%.

In [110]:

```
cm = confusion_matrix(y_test, y_pred)
plt.clf()
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Wistia)
classNames = ['Negative','Positive']
plt.title('Versicolor or Not Versicolor Confusion Matrix - Test Data')
plt.ylabel('True label')
plt.xlabel('Predicted label')
tick_marks = np.arange(len(classNames))
plt.xticks(tick_marks, classNames, rotation=45)
plt.yticks(tick_marks, classNames)
s = [['TN','FP'], ['FN', 'TP']]
for i in range(2):
    for j in range(2):
        plt.text(j,i, str(s[i][j])+" = "+str(cm[i][j]))
plt.show()
```



In [108]:

```
param_grid_dt = {"max_depth" : [1, 5, 10, 15, 20, 25, 30],
                 "min_samples_leaf" : [1, 2, 4, 6, 8, 10]}
# create and fit a ridge regression model, testing each alpha
model = DecisionTreeClassifier()
grid = model_selection.GridSearchCV(estimator=model, param_grid=param_grid_dt)
grid.fit(X_train, y_train)
print(grid)
# summarize the results of the grid search
print(grid.best_score_)
print(grid.best_estimator_)
```

```
GridSearchCV(cv='warn', error_score='raise-deprecating',
             estimator=DecisionTreeClassifier(class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features=None,
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
```

```
                                            presort=False, random_state=None,
                                            splitter='best'),
             iid='warn', n_jobs=None,
             param_grid={'max_depth': [1, 5, 10, 15, 20, 25, 30],
                         'min_samples_leaf': [1, 2, 4, 6, 8, 10]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
0.9664741449327678
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=10,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=8, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

In [115]:

```
# unscaled Decision Tree with Bagging
# Bagging of the classifiers (unscaled)
bg = BaggingClassifier(DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=10,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=8, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best'),
                       max_samples=0.5, max_features=1.0, n_estimators=20, random_state=seed)
bg.fit(X_train, y_train)
print("Bagging of DeicionTreeClassifier after GridSearchCV:", bg.score(X_test, y_test))
```

```
Bagging of DeicionTreeClassifier after GridSearchCV: 0.9711243457859592
```

Conclusion (1):

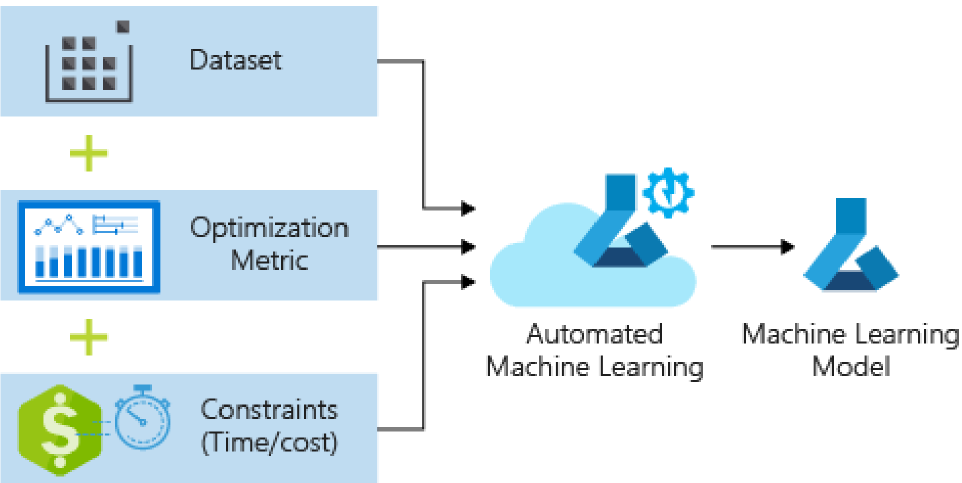
The best model found for predicting bankruptcy was BaggingClassifier with DecisionTreeClassifier with the unscaled data, which resulted in a score of 97.13%. The default DecisionTree was used first for the different classifiers and then Bagging. The GridSearchCV was additionally used at the end to compare/test. It gave the optimal parameters, but the score was 97.11% which was very similar to default parameters.

AutoML: Automatic Machine Learning

In [121]:

```
from IPython.display import Image
from IPython.core.display import HTML
Image(url= "https://i0.wp.com/softwareengineeringdaily.com/wp-content/uploads/2019/05/image7-1.png
?fit=469%2C235&ssl=1", width=600, height=200)
```

Out[121]:



- H2O is a Java-based software for data modeling and general computing
- The goal of H2O is to allow simple horizontal scaling to a given problem in order to produce a solution faster

- The goal of H2O is to allow simple horizontal scaling to a given problem in order to produce a solution faster
- The conceptual paradigm MapReduce (AKA "divide and conquer and combine"), along with a good concurrent application structure, (c.f. jsr166y and NonBlockingHashMap) enable this type of scaling in H2O

AutoML is a technique widely used by companies now for efficiency

Reference: http://docs.h2o.ai/h2o/latest-stable/h2o-py/docs/intro.html

In [4]:

```
import h2o
from h2o.automl import H2OAutoML
h2o.init()
```

```
Checking whether there is an H2O instance running at http://localhost:54321 ..... not found.
Attempting to start a local H2O server...
; Java HotSpot(TM) 64-Bit Server VM (build 25.231-b11, mixed mode)
  Starting server from C:\Users\ankur\Anaconda3\lib\site-packages\h2o\backend\bin\h2o.jar
  Ice root: C:\Users\ankur\AppData\Local\Temp\tmpkcd7pwd4
  JVM stdout: C:\Users\ankur\AppData\Local\Temp\tmpkcd7pwd4\h2o_ankur_started_from_python.out
  JVM stderr: C:\Users\ankur\AppData\Local\Temp\tmpkcd7pwd4\h2o_ankur_started_from_python.err
  Server is running at http://127.0.0.1:54321
Connecting to H2O server at http://127.0.0.1:54321 ... successful.
```

H2O cluster uptime:	04 secs
H2O cluster timezone:	-05:00
H2O data parsing timezone:	UTC
H2O cluster version:	3.26.0.6
H2O cluster version age:	16 days
H2O cluster name:	H2O_from_python_ankur_85pcdc
H2O cluster total nodes:	1
H2O cluster free memory:	3.528 Gb
H2O cluster total cores:	8
H2O cluster allowed cores:	8
H2O cluster status:	accepting new members, healthy
H2O connection url:	http://127.0.0.1:54321
H2O connection proxy:	None
H2O internal security:	False
H2O API Extensions:	Amazon S3, Algos, AutoML, Core V3, TargetEncoder, Core V4
Python version:	3.7.3 final

In [ ]:

```
h2o.demo("glm")
```

```
--------------------------------------------------------------------------------
Demo of H2O's Generalized Linear Estimator.

This demo uploads a dataset to h2o, parses it, and shows a description.
Then it divides the dataset into training and test sets, builds a GLM
from the training set, and makes predictions for the test set.
Finally, default performance metrics are displayed.
--------------------------------------------------------------------------------

>>> # Connect to H2O
>>> h2o.init()

(press any key)
```

In [5]:

```
# concanetate all 5 years and preprocess same as earlier
df = pd.concat([data1[0], data1[1], data1[2], data1[3], data1[4]])
print("Data size:", df.shape)
```

```
cont_names = df.columns[:-1]
df.rename(columns={'class':'target'}, inplace=True)
df.replace({'target': b'1'}, int(1), inplace=True)
df.replace({'target': b'0'}, int(0), inplace=True)
df['Attr55'] = None

# split again
X_train, X_test, y_train, y_test = train_test_split(df[cont_names], df['target'], test_size=0.2, ra
ndom_state=42)
train = pd.concat([X_train, y_train], 1)
test = pd.concat([X_test, y_test], 1)
```

```
Data size: (43405, 65)
```

In [6]:

```
df = h2o.H2OFrame(train)
```

```
Parse progress: |█████████████████████████████████████████████████████████| 100%
```

In [7]:

```
df['target'] = df['target'].asfactor()
y = "target"
cont_names = cont_names.tolist()
x = cont_names
```

In [8]:

```
# max_runtime_secs= 3600, sort_metric='AUC'
aml = H2OAutoML(max_runtime_secs= 3600*6, max_models=60, sort_metric='AUC')
aml.train(x = x, y = y, training_frame = df)
```

```
AutoML progress: |████████████████████████████████████████████████████████| 100%
```

In [9]:

```
# entire leaderboard
lb = aml.leaderboard
lb.head(rows=lb.nrows)
```

model_id	auc	logloss	mean_per_class_error	rmse	mse
StackedEnsemble_AllModels_AutoML_20191018_010439	0.948751	0.0972429	0.216458	0.154564	0.02389
GBM_5_AutoML_20191018_010439	0.946161	0.0942537	0.215193	0.158331	0.0250687
GBM_4_AutoML_20191018_010439	0.946021	0.0936558	0.215576	0.156588	0.0245199
GBM_grid_1_AutoML_20191018_010439_model_1	0.944657	0.0946913	0.215989	0.156215	0.0244031
StackedEnsemble_BestOfFamily_AutoML_20191018_010439	0.943432	0.104968	0.226863	0.161392	0.0260473
GBM_grid_1_AutoML_20191018_010439_model_7	0.942182	0.10055	0.231349	0.162314	0.0263457
GBM_3_AutoML_20191018_010439	0.941153	0.0943815	0.234808	0.156434	0.0244716
GBM_grid_1_AutoML_20191018_010439_model_24	0.939322	0.105565	0.227787	0.167913	0.0281946
GBM_grid_1_AutoML_20191018_010439_model_17	0.936824	0.103113	0.243774	0.165732	0.0274672
GBM_2_AutoML_20191018_010439	0.935992	0.0976685	0.236548	0.158774	0.0252091
GBM_grid_1_AutoML_20191018_010439_model_18	0.924321	0.107451	0.262395	0.166388	0.027685
GBM_grid_1_AutoML_20191018_010439_model_14	0.924148	0.104833	0.254957	0.162949	0.0265524
GBM_1_AutoML_20191018_010439	0.920535	0.108111	0.243346	0.165551	0.027407
GBM_grid_1_AutoML_20191018_010439_model_11	0.91675	0.11391	0.266558	0.171541	0.0294264
GBM_grid_1_AutoML_20191018_010439_model_21	0.91136	0.122688	0.266753	0.178509	0.0318655
GBM_grid_1_AutoML_20191018_010439_model_26	0.910763	0.133259	0.261291	0.188245	0.0354363
GBM_grid_1_AutoML_20191018_010439_model_2	0.905486	0.155071	0.316114	0.198876	0.0395517
GBM_grid_1_AutoML_20191018_010439_model_15	0.902005	0.118664	0.28579	0.173093	0.0299612

model_id	auc	logloss	mean_per_class_error	rmse	mse
GBM_grid_1_AutoML_20191018_010439_model_6	0.897719	0.134306	0.305691	0.187236	0.0350574
GBM_grid_1_AutoML_20191018_010439_model_4	0.88979	0.142817	0.275585	0.193568	0.0374684
GBM_grid_1_AutoML_20191018_010439_model_20	0.889086	0.125334	0.312457	0.178092	0.0317169
XRT_1_AutoML_20191018_010439	0.882363	0.132751	0.325001	0.185164	0.0342859
GBM_grid_1_AutoML_20191018_010439_model_23	0.87959	0.130851	0.309815	0.180928	0.0327348
GBM_grid_1_AutoML_20191018_010439_model_12	0.879068	0.168485	0.325068	0.205532	0.0422433
DRF_1_AutoML_20191018_010439	0.878951	0.134824	0.333702	0.187007	0.0349717
GBM_grid_1_AutoML_20191018_010439_model_5	0.876669	0.142443	0.319838	0.192355	0.0370004
GBM_grid_1_AutoML_20191018_010439_model_9	0.865953	0.179259	0.290822	0.209562	0.0439163
GBM_grid_1_AutoML_20191018_010439_model_3	0.86525	0.17553	0.324683	0.207969	0.0432509
GBM_grid_1_AutoML_20191018_010439_model_13	0.863122	0.154038	0.331081	0.19934	0.0397365
GBM_grid_1_AutoML_20191018_010439_model_19	0.855623	0.1648	0.321445	0.196691	0.0386873
GBM_grid_1_AutoML_20191018_010439_model_10	0.844549	0.155594	0.321036	0.19963	0.039852
GBM_grid_1_AutoML_20191018_010439_model_22	0.829956	0.182629	0.335396	0.210514	0.044316
GBM_grid_1_AutoML_20191018_010439_model_16	0.82308	0.181876	0.357154	0.210253	0.0442065
DeepLearning_grid_1_AutoML_20191018_010439_model_1	0.814355	0.175703	0.369604	0.196201	0.038495
DeepLearning_1_AutoML_20191018_010439	0.807011	0.166803	0.346331	0.199365	0.0397463
GBM_grid_1_AutoML_20191018_010439_model_25	0.794918	0.7468	0.304263	0.256174	0.0656251
GBM_grid_1_AutoML_20191018_010439_model_8	0.781634	0.188762	0.345668	0.2122	0.0450287
GLM_grid_1_AutoML_20191018_010439_model_1	0.578259	0.189724	0.451357	0.212406	0.0451164

Out[9]:

In [10]:

```
hf = h2o.H2OFrame(test)
preds = aml.predict(hf)
preds = preds.as_data_frame()
preds['p_p0'] = np.exp(preds['p0'])
preds['p_p1'] = np.exp(preds['p1'])
preds['sm'] = preds['p_p1'] / (preds['p_p0'] + preds['p_p1'])
```

```
Parse progress: |█████████████████████████████████████████████████████████| 100%
stackedensemble prediction progress: |████████████████████████████████████| 100%
```

In [11]:

```
from sklearn.metrics import roc_auc_score

roc_auc_score(y_test, preds['sm'])
```

Out[11]:

```
0.9500382515465734
```

Conclusion (2):

The H2O module being used has an AutoML workflow to automatically train and tune several models and provide us the statistical results. The workflow parameters were chosen as (max_runtime_secs= 3600* 6, max_models=60, sort_metric='AUC') to get these results. Like always, tuning this depends on the computer power but this shows a good idea.